Precipitation Estimation Using L-Band and C-Band Soil Moisture Retrievals

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Key Points:

- Information on the time sequencing of precipitation rates is successfully extracted from four soil moisture retrieval datasets.

- This information is of unprecedented accuracy for the L-band retrievals, presumably because they are sensitive to emissions from deeper in the soil.

- The relative performance amongst the L-band datasets can be explained by known features of the instruments and algorithms.

Abstract

An established methodology for estimating precipitation amounts from satellite-based soil moisture retrievals is applied to L-band products from the Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS) satellite missions and to a C-band product from the Advanced Scatterometer (ASCAT) mission. The precipitation estimates so obtained are evaluated against *in situ* (gauge-based) precipitation observations from across the globe. The precipitation estimation skill achieved using the L-band SMAP and SMOS datasets is higher than that obtained with the C-band product, as might be expected given that L-band is sensitive to a thicker layer of soil and thereby provides more information on the response of soil moisture to precipitation. The square of the correlation coefficient between the SMAP-based precipitation estimates and the observations (for aggregations to ~100 km and 5 days) is on average about 0.6 in areas of high rain gauge density. Satellite missions specifically designed to monitor soil moisture thus do provide significant information on precipitation variability, information that could contribute to efforts in global precipitation estimation.

1. Introduction

The potential societal benefits of an accurate estimation of precipitation – its magnitudes and its variations in time – are immense. Precipitation data are crucial for crop modeling and forecasting, water resources planning, soil moisture initialization for weather forecasts and seasonal forecasts, flood and landslide analysis, and a host of other valuable applications. Precipitation is indeed the key driver of surface hydrological processes and is an essential link between the land and atmospheric components of the climate system.

The importance of measuring precipitation accurately has not been lost on the scientific community. A number of projects over the years have produced global-scale precipitation data for scientific and technical applications. Key datasets are available, for example, from the National Center for Environmental Prediction [*Xie et al.* 2007, also ftp://ftp.cpc.ncep.noaa.gov/precip/cmap/] and the Global Precipitation Climatology Project [*Adler et al.* 2003], the latter being sponsored by the Global Climate Research Programme. To produce the global-scale gridded precipitation rates, such projects utilize a number of data sources, including rain gauges, satellite-based precipitation retrievals, and model analysis products. Satellite-based estimates of precipitation are indeed becoming more and more relevant, with valuable data provided by the Tropical Rain Measurement Mission [TRMM, *Huffman et al.* 2007] and the follow-on Global Precipitation Mission (http://www.nasa.gov/mission_pages/GPM/main/index.html).

Advances in technologies notwithstanding, all current precipitation estimation techniques have limitations. Rain gauges are generally considered to be the most accurate source of precipitation data [*Huffman et al.* 1997], but they represent local measurements and, given issues of spatial representativeness, are not always easily translated to area-averaged precipitation rates.

Rain gauges are also absent in many parts of the world. Satellite-based precipitation rates, while clearly valuable, are limited by the "snapshot" character of the individual measurements and by various difficulties in interpreting satellite signals over land [*Hou et al.* 2014, *Kummerow et al.* 2015]. Analysis products from atmospheric models, for their part, are subject to the biases inherent in the underlying models used. Given such issues, alternative methods of estimating precipitation could prove valuable. Indeed, using data from a proven alternative method in concert with satellite-based precipitation retrievals, rain gauge measurements, and analysis products, properly taking into account the relative strengths and weaknesses of each method, could yield a superior global precipitation dataset that could benefit many user applications.

One particularly promising and currently under-utilized data source relevant to precipitation estimation is soil moisture as measured from space. The potential for extracting precipitation information from space-based soil moisture retrievals is illustrated in Fig. 1, which shows time series of Level 2 passive soil moisture retrievals from the Soil Moisture Active-Passive mission (SMAP; see section 2a below) plotted alongside spatially collocated gauge-based precipitation data at a western U.S. site. SMAP surface soil moisture values (top ~5 cm of soil) are represented as red dots, and the precipitation rates, from the Climate Prediction Center Unified rain gauge dataset (see section 2b), are shown as blue histogram bars. Soil moisture is seen to increase at the onset of precipitation (e.g., on days 117, 133, 155, and 184), with larger increases for larger precipitation rates (compare the increases on days 133 and 155). Furthermore, following the cessation of rain, soil moisture gradually reduces to a value near zero. The overall consistency between the independent soil moisture and precipitation data is high; the retrievals here do contain useful information on the time sequencing and relative magnitudes of precipitation events.

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94   Recognizing this connection, several studies have in fact presented approaches for

95 utilizing satellite-based soil moisture data to improve existing precipitation datasets [e.g., *Crow*

96 *et al.* 2009, 2011; *Pellarin et al.* 2008, 2013; *Wanders et al.* 2014; *Zhan et al.* 2015]. In the

97 present study we consider a distinctly different class of algorithm: one that uses soil moisture

98 retrievals in isolation to compute an independent time series of precipitation for direct

99 comparison with existing data from more traditional sources (e.g., rain gauges or satellites). This

100 use of soil moisture as a virtual rain gauge was pioneered by *Brocca et al.* [2013], who

101 developed a specific algorithm, called SM2RAIN, for generating time series of precipitation

102 rates based on the changes seen in consecutive soil moisture retrievals (see section 2c). *Brocca*

103 *et al.* [2014] applied this algorithm to Advanced Scatterometer (ASCAT) and Advanced

104 Microwave Scanning Radiometer – EOS (AMSR-E) soil moisture retrievals and to an early

105 version of SMOS (Soil Moisture Ocean Salinity) retrievals and found that the resulting

106 precipitation time series were promisingly realistic.

107   The launch in 2015 of the SMAP soil moisture satellite and the considerable updates in

108 the processing of the SMOS products (since the *Brocca et al.* [2014] study) provides a valuable

109 opportunity to evaluate this precipitation estimation approach with presumably more accurate

110 soil moisture retrievals. SMAP and SMOS are both L-band instruments and thereby extract soil

111 moisture information from deeper in the soil than C-band instruments such as AMSR-E or

112 ASCAT (~5 cm versus ~2 cm), allowing for a more complete characterization of how soil

113 moisture responds to precipitation. The SMAP mission, in addition, has numerous protocols in

114 place to reduce noise from radio frequency interference [RFI, *Entekhabi et al.* 2010]. The

115 present paper aims to quantify the level of precipitation estimation accuracy achievable using

these new L-band instruments relative to that achievable with a representative C-band instrument.

Section 2 describes the datasets used and outlines the SM2RAIN precipitation estimation algorithm, including special modifications adopted for this study. Section 3 presents the accuracies achieved with the L-band and C-band data, and section 4 provides a summary and further discussion.

2. Data and Methods

2.1 Satellite Retrievals

2.1.1. *SMAP*

The SMAP satellite, launched in early 2015, carries an L-band radar and radiometer that provide global radar backscatter and brightness temperature observations every 2-3 days. The radar ceased operation on 7 July 2015, but the radiometer continues to operate well. Amongst other products, SMAP retrieves the soil moisture content of the upper ~5 cm of soil. SMAP was designed with a sun-synchronous orbit with 6 AM/PM local equatorial overpass time and has a nominal incidence angle of 40°.

The specific SMAP data used in this study are the Level 2 retrievals (L2_SM_P) from the passive radiometer [*Entekhabi et al.* 2010, *Chan and Dunbar* 2015]. The passive-based soil moisture data are provided on a 36 km Earth-fixed grid using the global cylindrical Equal-Area Scalable Earth Grid Projection Version 2 [EASEv2, *Brodzik et al.* 2012]. We use in particular the "beta release" version of these data [*O'Neill et al.* 2014], the most advanced version available

to us at the time of this writing. These data are limited to the descending swaths of the SMAP

data, corresponding to local retrieval times of 6 AM. The retrievals are obtained using the Single

Channel Algorithm [*Jackson et al.* 2015] and are currently based on V-polarized brightness

temperature observations only. We excluded coastal pixels from our analysis, and we considered

only those retrievals that have been flagged as "attempted" and "successful". To allow greater

global coverage, however, we ignored the flag associated with "recommended quality". We also

ignored flags indicating the potential presence of snow or frozen soil; given the time period

considered (May for calibration, and mid-June through mid-October for validation, as discussed

below), this should have minimal impact on our results over most of the globe.

2.1.2. *SMOS-A and SMOS-D*

SMOS [*Kerr et al.* 2010], launched in early November 2009, carries an L-band

radiometer and primarily maps soil moisture and ocean salinity. It observes the Earth in a sun-

synchronous orbit at 6 AM/PM local overpass time at incidence angles ranging from 0° to 65°,

and, like SMAP, it has a temporal revisit of 2-3 days and a nominal spatial resolution of about 40

km. For this study we use Level 2 retrieval data from the SMOS SMUDP2 product version v620.

The SMOS retrieval algorithm simultaneously retrieves soil moisture and other variables, such as

the vegetation opacity, by fitting multi-angular brightness temperatures at both horizontal and

vertical polarization with L-band Microwave Emission of the Biosphere [L-MEB, *Wigneron et*

al. 2007] model simulations. Data were retained only if: (a) all retrieved variables fall within a

realistic range (0-0.8 m^3/m^3 for soil moisture), (b) the retrieval uncertainty is less than a certain

threshold (0.1 m^3/m^3 for soil moisture), (c) the RFI-probability for both H-and V-polarization is

less than 0.3, and (d) flags are not raised for high topographic complexity, high urban fraction,

high open water fraction, sea ice, coastal areas, and high total electron content. The SMOS data were regridded from a 12.5 km posting resolution to the 36-km EASEv2 grid; during this aggregation step, the data were screened for excessive sub-36-km heterogeneity (spatial standard deviation > 0.5 m^3/m^3) that may be indicative of RFI or the presence of open water bodies.

We use two distinct SMOS datasets in this study: SMOS-A, consisting of data collected on ascending passes of the satellite (corresponding to 6AM local time), and SMOS-D, consisting of data collected on descending passes (corresponding to 6PM local time). The data are separated in this way because the timing of the overpass has a potentially significant impact on retrieval accuracy (see, e.g., *Lei et al.* [2015]). By using both SMOS datasets, we should be able to see if the expected increase in accuracy for SMOS-A translates to a corresponding increase in the accuracy of precipitation estimation.

2.1.3. *ASCAT*

ASCAT, a real aperture radar operating at C-band, was launched on board the European Meteorological Operational (MetOp)-B spacecraft in 2012. It observes the Earth in a sun-synchronous orbit at 9:30 AM/PM local overpass time, and it has a temporal revisit of 3 days. For this study, we took advantage of the availability of an ASCAT dataset already processed by the SMAP mission for comparison with SMAP morning retrievals. To construct this dataset, the 9:30 AM (descending) ASCAT L2 soil moisture index posted at 12.5 km resolution was re-gridded to EASEv2 at 36 km by averaging the data using inverse distance weighting for each day. ASCAT retrievals were masked out if the probability of snow, frozen ground, wetland, or significant topography exceeds 50% or if the soil moisture estimation uncertainty due to other sources exceeds 50%. The soil moisture index on EASEv2 at 36 km was converted to

volumetric soil moisture by multiplication with soil porosity, which was also delivered (at 9 km)

as ancillary data [*De Lannoy et al.* 2014, *Mahanama et al.* 2015] to the SMAP Level 4 soil

moisture product [*Entekhabi et al.* 2014].

2.2. Precipitation Data

The precipitation data used to evaluate the satellite-based precipitation estimates are from

the CPC (Climate Prediction Center) Unified Gauge-Based Analysis of Global Daily

Precipitation (hereafter CPCU; see

ftp://ftp.cpc.ncep.noaa.gov/precip/CPC_UNI_PRCP/GAUGE_GLB/). For this study, the daily

dataset was converted from its original 0.5°× 0.5° grid to the SMAP EASEv2 grid at 36 km using

areal weighting.

As its name implies, the CPCU data are based on rain gauges only; no satellite-based

rainfall information was used in the construction of the dataset. In focusing on the gauge-based

data, we implicitly assume that it is the most accurate data available. Indeed, gauge-based data

are generally used to validate satellite-based precipitation retrievals [*Huffman et al.* 1997]. The

usefulness of the dataset for validation is nevertheless limited in regions of low rain gauge

density. Fig. 2 shows the rain gauge density associated with the CPCU data used. High densities

are seen in much of North America and Europe and in various parts of the other continents. On

the other hand, low densities appear, for example, in high northern latitudes, in the Amazon, and

in most of Africa. In such low-density regions, we cannot pretend to know (from the CPCU

dataset or, arguably, from gauge-based precipitation datasets in general) what the true daily

precipitation rates are. We will refer to the density map in Fig. 2 as we proceed with our

analyses. Note that the map uses density units of #gauges/0.5°×0.5°-cell; these densities, with no change in units, are re-gridded using areal weighting to the finer EASEv2 grid at 36 km for use in evaluating our precipitation estimation accuracy.

Another important issue regarding the CPCU precipitation data involves the reporting time for the daily values, which differs by region – some regions may report values for 6AM-6AM local time to the CPCU data collectors, others may report calendar-day values, and so on. To reduce the impact of the potential inconsistency between the gauge precipitation measurements and the retrieval-based estimates, we will focus our validation on 5-day precipitation totals; for each day in the validation period, we compare the estimated total precipitation from two days prior to two days after the reported date to the corresponding total from CPCU. Through such a procedure, of course, some inconsistency may still remain on Day -2 and Day +2. Note that this remaining inconsistency can only reduce the computed precipitation estimation skill levels, so that true skill levels may in fact be higher than those established here.

Finally, we do not attempt here to separate the observed precipitation rates into rainfall and snowfall rates. Again, given the time period considered in this analysis (northern hemisphere warm season), this should have limited impact on our results over most of the globe.

2.3. The SM2RAIN Precipitation Estimation Algorithm

In its basic form, the SM2RAIN algorithm [*Brocca et al.* 2013] estimates the precipitation, P_{est}, for each day between retrieval times t-1 and t using an equation equivalent to:

$$P_{est} = \alpha \, \text{Max}\{\, 0., \ [\, (W_t - W_{t-1}) / \Delta t \ + \ 0.5 \, \gamma \, (W_t^b + W_{t-1}^b) \,] \,\} \tag{1}$$

10

231 where W_t and W_{t-1} are consecutive soil moisture retrievals (in volumetric units: m^3/m^3), Δt is the

232 time interval (in days) between them, and α, γ, and b are fitted constants (see below), with γ

233 having units that convert the second term within the brackets of Eq. (1) to units of $m^3/m^3/day$,

234 and α having units that convert the right-hand-side of Eq. (1) to mm/day. The term $(W_t-W_{t-1})/\Delta t$

235 is positive if soil moisture increases between t-1 and t; this increase is indicative of a

236 precipitation event and thus adds to the value of P_{est}. The term $0.5\ \gamma\ (W_t^b + W_{t-1}^b)$ is included to

237 represent drainage, which can reduce surface soil moisture even during precipitation events.

238 Because this drainage is larger for wetter soils, precipitation has to "fight harder" to increase soil

239 moisture when the soil is wetter; this second term captures this effect. The presence of this term

240 allows (1) to estimate nonzero rainfall even when the soil moisture decreases slightly over the

241 time interval. (Note that the original equation in *Brocca et al.* (2013) only included the $\gamma\ W_t^b$

242 term; here, a second term is included to tie the assumed drainage to both the initial and final soil

243 moisture states, to approximate an average drainage.)

244   Of course, any such algorithm has an important limitation: its ability to capture high

245 precipitation rates is necessarily limited by the fact that soil moisture cannot exceed porosity, so

246 that any precipitation water that forms overland flow will necessarily be missed. Also, the

247 imprint of a given precipitation volume on a soil moisture retrieval will presumably depend on

248 how long before the retrieval the precipitation event occurred, and satellite retrievals in any case

249 contain error that will necessarily be propagated to the precipitation estimates. Even so, *Brocca*

250 *et al.* [2014] demonstrate a successful application of the algorithm to ASCAT data, and, as will

251 be shown in the following section, the algorithm performs even better with SMAP and SMOS

252 data.

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2.4. Application of SM2RAIN to SMAP, SMOS, and ASCAT data

2.4.1. *Skill Metric*

Our metric for evaluating the algorithm's ability to estimate precipitation is the square of the correlation coefficient (r^2) between our precipitation estimates from Eq. (1) and corresponding observed (gauge-based) precipitation rates. Thus, in this paper, we are evaluating the estimation of the time sequencing of precipitation and the associated capture of the relative magnitudes of different storms rather than the absolute magnitudes of the rates, as would be addressed with a root-mean-square-error metric. By using an r^2 metric, we are in fact evaluating a quantity that is directly proportional to the actual precipitation rate, which has the distinct advantage of reducing from 3 to 2 the number of parameters needing calibration in Eq. (1) – there is no need to calibrate the scale factor α. When it comes time to producing actual precipitation estimates, our estimates would need to be scaled accordingly, presumably in a very simple way using ratios of long-term observed precipitation totals to long-term estimate totals, either in the region of interest or, for a region without adequate precipitation measurement, in a region of similar soil texture. Alternatively, the information contained in the (unscaled) time sequences could be used directly in conjunction with other precipitation time series (e.g., from rain gauges, satellite missions focused on rainfall) to produce improved hybrid datasets – a distinct possibility if the soil moisture-based information is determined to be significant through the r^2 metric.

The satellite soil moisture retrievals are not available on a daily basis; they are often separated by two or three days. The effective temporal resolution of the associated SM2RAIN precipitation estimates is necessarily tied to these retrieval times. In our analyses, if two

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consecutive retrieval intervals are separated by N days, the resulting SM2RAIN estimate of precipitation rate from (1) is assigned to each of those N days. As noted in section 2.2, we further coarsen the resulting daily time series of estimated precipitation rates to a sequence of 5-day averages, which we compare to corresponding 5-day averages of rain gauge data from the CPCU dataset.

2.4.2. *Special Modifications of the Basic Algorithm*

In practice, different sets of values for the parameters in (1) can be determined for different regions of the world. *Brocca et al.* [2014] indeed use different climatic precipitation classes to define different parameter sets. For this study, however, we emphasize simplicity and robustness; we determine a single set of parameters that can be used everywhere across the globe. Going to region-specific or hydrological regime-specific parameter sets would theoretically only increase our computed estimation accuracies.

Using a single set of parameters makes it necessary, when processing the satellite retrievals, to standardize soil moisture contents by: (i) determining, at each grid element, the minimum soil moisture obtained over the period of record, and then (ii) subtracting this value from each retrieval at that grid element. In conceptual terms, such a calculation has both an advantage and a disadvantage. The advantage is that it addresses the fact that different locations on the globe may (at least for certain retrieval datasets) have different soil moisture minima, as a function, for example, of soil texture. The subtraction in effect provides all locations with a single common baseline – any soil moisture above the baseline, anywhere across the globe, has the potential to decrease during an interstorm period. The disadvantage is that many locations may never experience their true minimum value during the period of record, so that the baseline

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utilized for them is inaccurate. We proceed with full knowledge of this disadvantage, knowing

that the inaccuracy would eventually be reduced as more satellite data are collected, and

furthermore realizing that the inaccuracy, as it currently exists, can only degrade the performance

of our present calculations. If the precipitation algorithm is shown now to perform well despite

the inaccuracy in the estimated baseline soil moisture, then the inaccuracy can be assumed

unimportant.

2.4.3. *Algorithm Calibration and Validation*

For each of the satellite-based soil moisture retrieval datasets (SMAP, SMOS-D, SMOS-

A, and ASCAT), we use the period May 5-31, 2015 (a period defined by mutual data

availability) to calibrate the parameters γ and *b* in (1). Because we are using an r^2 metric, an

arbitrary value for the parameter α is assigned. Our calibration procedure involves computing

May precipitation time series using (1) for each of a great many potential pairings in the [γ, b]

parameter space and determining the pairing for which the global average of the r^2 skill metric

for May (in regions with a rain gauge density of at least 1 gauge per 0.5° grid cell) is the largest.

The calibrated parameter values are then used to estimate precipitation over the period June 20 to

October 15. (Part of June is skipped in accordance with the European Space Agency's

recommendation to avoid this particular data period for SMOS; see

https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/smos/news/-/article/smos-

level-1-and-2-data-products-short-period-of-degraded-data.)

3. Results

323   The red dots in Fig. 3a show the time series of SMAP soil moisture retrievals at a

324   representative location in the central US (a farmland region in southwestern Kansas). The dark

325   blue histogram bars in Fig. 3a show the precipitation time series estimated from these retrievals

326   using (1). Careful study of these data shows that nonzero precipitation is indeed sometimes

327   estimated with (1) even during periods of decreasing soil moisture, especially when the initial

328   soil moisture is high.

329   Fig. 3b shows, with dark blue hollow histogram bars, the corresponding time series of the

330   SM2RAIN estimates averaged over 5-day periods. Plotted as light blue solid histogram bars are

331   the observed 5-day precipitation totals from the CPCU rain gauge dataset. The time series show

332   some similarity; the r^2 between the estimated and observed time series in Fig. 3b is 0.55,

333   indicating some skill in the estimation of precipitation from the soil moisture retrievals alone –

334   over 50% of the observed precipitation variance is explained by our precipitation estimates.

335   This basic calculation underlies Figs. 4a-d, which show the global distributions of r^2 for

336   5-day precipitation rates estimated from the SMAP, SMOS-A, SMOS-D, and ASCAT datasets,

337   respectively. Note that at some locations (shown in white), r^2 values could not be determined

338   due to limitations in the precipitation data or in the soil moisture retrieval data (e.g., high levels

339   of RFI). High r^2 values (exceeding 0.6) are seen, for example, in much of the continental U.S.

340   and Europe and in parts of western Asia, Australia, southern Africa, and South America,

341   particularly for SMAP. Lower r^2 values are seen elsewhere, but these do not necessarily imply a

342   deficiency in the technique – rather, they are at least partly indicative of deficiencies in the

343   precipitation observations (i.e., the validation data) themselves. This can be seen by comparing

344   the fields in Fig. 4 with the map of rain gauge density in Fig. 2. The r^2 fields are strongly

345   determined by rain gauge density, with high r^2 values generally found in regions of high density

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346 and low values in regions of low or zero density. We can reasonably argue that the true

347 precipitation is simply not well known in areas with low gauge density and that, if the true

348 precipitation were in fact known better in these regions, the skill found for the satellite-based

349 estimates there would be much larger.

350 　　We can increase skill levels further by addressing spatial representativeness error. As

351 described above, averaging the daily precipitation estimates to 5-day totals allows us to address

352 some of the representativeness errors associated with inconsistencies in the timing of satellite

353 overpasses and precipitation rain gauge measurements. Some representativeness errors,

354 however, also exist in the spatial domain – rain gauges provide point measurements that may be

355 inconsistent with the areal averages computed with the estimation algorithm, particularly in areas

356 of lower gauge density. Furthermore, while the nominal (3 dB) resolution of, for example,

357 SMAP and SMOS is ~40 km, the integrated signal in fact comes from a circular area with a

358 diameter of ~80 km, with less weight in the outer area. To address (at least to some extent) these

359 issues, we now compute correlations after aggregating both the retrieval-based precipitation

360 estimates and the gridded rain gauge measurements to a coarser (~100 km, or about 1°) spatial

361 scale: over 3×3 blocks of EASEv2 grid cells.

362 　　Fig. 5 shows the results for all four retrieval datasets. The increase in the r^2 values is

363 striking. As expected, values are still low in areas of low rain gauge density (as presumably they

364 must be), but r^2 values are high across much of North America, Europe, and western Asia and are

365 also high in many parts of the other continents. For SMAP, for example, the r^2 values in these

366 regions often exceed 0.7 – over much of the globe (~24% of the globe with a gauge density of at

367 least 1 gauge per 0.5° grid cell), the SMAP-based estimates "explain" 70% or more of the

368 variance in the observed 5-day precipitation rates.

369   Of particular interest is the relative performance of the four datasets. Figs. 4 and 5

370   indicate that of the four retrieval datasets examined, SMAP produces the most accurate

371   precipitation estimates, followed by SMOS-A, with both performing better than SMOS-D and

372   ASCAT. This relative performance is also apparent in the global averages of the skill levels

373   shown in Fig. 5: for ~100 km averages, the average r^2 skill levels obtained over land areas for

374   SMAP, SMOS-A, SMOS-D and ASCAT are, respectively, 0.35, 0.29, 0.25, and 0.27. (Note that

375   r^2 values are not computed in the whited out regions of the maps due to the presence of open

376   water [exceeding a fraction of 0.05, according to SMAP estimates] or to other data limitations,

377   such as those associated with RFI for SMOS. For a consistent comparison, the above global

378   averages were computed across the same set of grid cells for each satellite dataset – the set of

379   cells holding a defined value for each dataset.) Averaging instead over land areas with a gauge

380   density of 1 gauge or more per 0.5° grid cell naturally gives higher (and more physically

381   meaningful) averages: 0.58, 0.51, 0.43, and 0.42 for SMAP, SMOS-A, SMOS-D, and ASCAT,

382   respectively.

383   We generalize further the relative skill levels of the different datasets and the impact of

384   rain gauge density on this skill in Fig. 6. For a given satellite retrieval dataset, and for both the

385   36-km and aggregated ~100-km resolutions, we compute the average of the precipitation

386   estimation skill (r^2) over all land points having a gauge density within a stated range. Over 1000

387   values contribute to each average.

388   Two results are clearly evident from Fig. 6. First, for all retrieval datasets, precipitation

389   estimation skill increases with rain gauge density up to a density of about 1 gauge per 0.5° grid

390   cell, after which it either grows less quickly with density (SMAP and SMOS-A) or plateaus to a

391   roughly constant value (SMOS-D and ASCAT). Clearly, rain gauge density must be considered

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392 when evaluating the precipitation estimates. Second, the relative performance of the different

393 retrieval datasets remains largely as noted above. SMAP provides the highest skill levels

394 regardless of gauge density, followed by SMOS-A. SMOS-D and ASCAT perform similarly,

395 with ASCAT performing slightly better at low rain gauge densities.

396   What causes these differences in precipitation estimation skill between the retrieval

397 datasets? We can speculate that the differences are related to the inherent noise levels of the

398 datasets. All soil moisture retrievals are subject to some noise, and by *differencing* two

399 consecutive retrievals in (1), the impact of noise (particularly high frequency noise) on the

400 accuracy of the precipitation estimates is amplified. In simple terms, greater amounts of noise

401 must lead to reduced accuracy in precipitation estimation. Relative to the SMOS data, the

402 SMAP data arguably have reduced noise and thus a greater potential for accurate precipitation

403 estimation, given that the SMOS retrieval algorithm attempts to estimate multiple variables and

404 given the emphasis on RFI mitigation techniques built into the SMAP system [*Entekhabi et al.*

405 2010]. Given such considerations, the higher skill levels seen for SMAP make sense. It must be

406 kept in mind, however, that for applications not as affected by high frequency noise, the SMAP

407 and SMOS datasets have a presumably comparable usefulness.

408   Of the two SMOS datasets, SMOS-A is expected to be less noisy; Lei et al. [2016]

409 demonstrate that, for most of the continental United States, SMOS-A retrievals are more accurate

410 than SMOS-D retrievals. SMOS-A retrievals may have reduced noise due to the character of the

411 vertical temperature profile in the soil at the time of the retrievals. The SMOS-A data were

412 collected at 6AM, whereas the SMOS-D data were collected at 6PM; various studies [*e.g.,*

413 *O'Neill et al.,* 2014 (see their Figure 6)] suggest that at 6AM, vertical temperature profiles in the

414 soil, upon which retrieval algorithms are based, are roughly uniform, whereas at 6PM, strong

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vertical gradients exist that can make soil moisture estimation more difficult. (Note, however, that at least one study [*Hornbuckle and England*, 2005] found the opposite: more vertical uniformity in the evening.) Regardless of reason, assuming (following Lei at al. [2015]) that SMOS-A retrievals are less noisy, the higher precipitation estimation accuracy found for SMOS-A relative to SMOS-D makes sense, though the SMOS-D estimates presumably also incur reduced r^2 values from increased inconsistency with the CPCU gauge measurement times.

Again, both SMAP and SMOS are L-band instruments and thereby see emissions from deeper into the soil than C-band instruments such as ASCAT (~5 cm vs ~2 cm). In the context of characterizing the connection between soil moisture and precipitation, the increased depth is an advantage, for at least two reasons. First, the greater depth can distinguish a greater range of precipitation inputs – while a 1 cm rainfall event and a 2 cm event may both saturate a dry 2 cm layer (given a 50% porosity), the two events will produce distinctly different levels of soil moisture increase for a 5 cm layer. Second, deeper layers are characterized by greater persistence (e.g., *Koster and Suarez* [2001]); bare soil evaporation will reduce the average soil moisture content of a 2 cm layer more quickly than that of a 5 cm layer, and thus the latter can better retain information about a precipitation event if the event and the subsequent soil moisture retrieval are separated by, say, a couple of days. For these reasons, and because L-band measurements of emissions from the soil are less affected by the presence of vegetation than are C-band measurements, we expect the L-band instruments to perform better with the precipitation estimation algorithm. This expectation is borne out by the comparisons in Figs. 4-6.

At this point, it is worth revisiting the findings of *Brocca et al.* [2014], who quantified precipitation estimation skill levels for the C-band instruments of ASCAT and AMSR-E and for a previous version of the SMOS data, using 5-day and 1°×1° aggregates. Reprocessing the data

438 examined by *Brocca et al.* [2014] over a time period consistent with that used in this study (June

439 to October, although for 2010-2011), we find precipitation skill levels for ASCAT (not shown)

440 that are similar to those shown in Fig. 5d, though with some regional differences. Interestingly,

441 the ASCAT skill levels in the Sahel shown by *Brocca et al.* [2014] for all of 2010-2011 are

442 better than those for any of the sensors in Fig. 5, perhaps because the full 2010-2011 period

443 includes the sharp soil moisture transition associated with the Sahelian monsoon, which falls

444 outside of June-October. Re-processing the *Brocca et al.* [2014] ASCAT results for June-

445 October of 2010-2011 (not shown) significantly reduces Sahelian skill levels. Skill levels

446 obtained for AMSR-E for June-October of 2010-2011 (not shown) are substantially lower than

447 those for ASCAT and thus are substantially lower than those shown in Fig. 5 for any of the

448 sensors.

449 Curiously, the skill levels found by *Brocca et al.* [2014] for SMOS are substantially

450 lower than those presented here. Presumably this reflects our use here of a more recent version

451 of the SMOS data (we use SMUDP2 v620, whereas *Brocca et al.* [2014] used SMUDP2 v5.51)

452 and more detailed quality control, using recently updated information – an indication that the

453 reprocessing of such datasets, which is a standard part of such missions, can have a profoundly

454 positive impact. Recall that the SMAP data used in this paper are from a beta release, suggesting

455 the distinct possibility that future incarnations of the SMAP data could provide precipitation

456 estimates of even higher accuracy.

457

458 **4. Summary and Discussion**

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460   Application of the SM2RAIN algorithm to SMAP soil moisture retrievals produces time

461   series of precipitation with significant levels of accuracy across much of the globe (Figures 4a

462   and 5a). The average of the r^2 values for 5-day, ~1°×1° accumulated precipitation estimates

463   versus corresponding rain gauge observations is about 0.6 in parts of the globe for which the

464   precipitation measurements used for validation are particularly reliable (Fig. 6). These skill

465   levels are indeed unprecedented for soil moisture-based precipitation estimation, being

466   significantly higher than previously published values [*Brocca et al.* 2014]. Application of the

467   algorithm to the latest SMOS dataset (for ascending overpasses) produces slightly less accurate

468   precipitation rates, and application to ASCAT data produces even lower accuracies. The relative

469   levels of skill found for the retrieval datasets make sense in the context of their presumed relative

470   levels of high frequency noise: SMAP data, due to built-in RFI corrections, are expected to be

471   less noisy than SMOS data, and the L-band instruments (SMAP and SMOS) are expected to

472   produce less noise than C-band instruments because they deal better with moderate levels of

473   vegetation and because they see emissions from deeper in the soil, allowing a better discernment

474   of different rainfall volumes.

475   One question, however, not fully addressed here is whether the use of ASCAT ascending

476   data together with the descending data would have improved the skill levels produced for

477   ASCAT. Because the ASCAT retrievals are based on a change detection algorithm, and because

478   active products are less sensitive to land surface thermal conditions than are passive products,

479   soil temperature profiles are not a major issue for ASCAT, meaning that (in potential contrast to

480   SMOS) ascending and descending ASCAT retrievals should have similar quality. When we

481   reprocessed the 2010-2011 June-October ASCAT data examined by *Brocca et al.* [2014], which

482   do include both ascending and descending data, we found skill levels (not shown) similar to

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those in Fig. 5d, suggesting that use of the additional data would have had little effect. Still, the

following caveat is worth mentioning: a definitive C-band analysis that includes 2015 ascending

data has not yet been performed.

As illustrated in Fig. 6, rain gauge density is an important consideration in the evaluation

of the precipitation estimates. Our results indeed suggest that if precipitation rates were better

measured in the ungauged areas, the skill levels obtained there would be higher. This has

important implications. The high agreement in well-gauged areas suggests that retrieval-based

precipitation estimates could be used for various applications there in lieu of gauge-based

measurements, assuming enough observational precipitation data are available during a

calibration period to scale the retrieval-based estimates to the proper magnitudes. If such scaling

could be performed, then the retrieval-based precipitation estimates could themselves be used to

drive, for example, a river routing or crop growth model. Now consider relatively ungauged

regions (e.g., parts of the Sahel), for which the quality of the precipitation measurements is poor.

Assuming that the retrievals have the same basic accuracy everywhere, and assuming that scaling

factors obtained for well-gauged areas could be transferred to ungauged areas based on soil type

and other considerations, our results suggest that the retrieval-based precipitation estimates could

be applied to great advantage in these areas – the estimates would arguably be better than gauge-

based precipitation products.

This is, of course, an ambitious interpretation of the results. The retrieval-based

precipitation estimates would presumably be poor in tropical forests (e.g., the Amazon) given

known deficiencies of soil moisture retrievals in regions of dense vegetation. The retrievals may

also be poorer in ungauged regions because model-based surface temperature estimates in these

regions, a critical part of the retrieval algorithms (at least for SMOS and SMAP), may also be

506 poor. Still, given that precipitation is generally more difficult to capture correctly than

507 temperature, the interpretation is worth exploring with further study.

508 In any case, as noted in the introduction, perhaps the greatest value of the soil moisture-

509 based precipitation estimates lies in their potential combination with alternative precipitation

510 estimates to produce a single, superior precipitation dataset. This potential depends in large part

511 on the degree to which the soil moisture-based estimates provide unique and complementary

512 information about the temporal and spatial distributions of precipitation in nature. Devising an

513 optimal strategy for combining the soil moisture-based estimates with those from, for example,

514 gauge networks and satellite-based precipitation retrievals is beyond the scope of this paper;

515 note, however, that relevant issues have been discussed in several recent studies (e.g., Crow et al.

516 2011, Pellarin et al. 2013, Ciabatta et al. 2015, Zhan et al. 2015). Here we can address the

517 complementarity of the information content by pointing to the strengths and weaknesses of each

518 estimation approach.

519 Again, as noted in the introduction, in situ gauge measurements, while providing direct

520 (and thus high quality) measurements at gauge sites at high time resolution, are point

521 measurements and do not necessarily capture well the precipitation that falls across large areas.

522 Gauges are, in any case, sparse or wholly absent in many parts of the globe. Satellite-based

523 precipitation measurements (e.g., from GPM) provide high temporal (e.g., half-hourly) and

524 spatial resolution (e.g., 0.1°) data but to some degree are limited by both the "snapshot" nature of

525 the different contributing measurements (thereby potentially missing rainfall amounts falling

526 between the snapshots) and by difficulties, for example, in interpreting the relevant radiances

527 over land.

23

528   The advantages and disadvantages of the soil moisture-based precipitation estimation

529 approach are quite different. Disadvantages include a relatively coarser temporal resolution (2-3

530 days), as determined by the timespan between soil moisture retrievals. The estimates also

531 necessarily miss any rainfall that: (i) runs directly off the surface, e.g. during heavy storms or as

532 encouraged by complex terrain (though as suggested by Crow et al. [2011], this impact may be

533 minimal at the spatial scales considered here), or (ii) infiltrates quickly to deeper soil layers or

534 evaporates quickly from the surface before the next soil moisture retrieval is captured. In

535 addition, errors in soil moisture estimation at L-band and C-band are known to be large over

536 dense vegetation and certain other surface types, meaning that the precipitation estimates in

537 certain regions will be questionable. The advantages, however, of the soil moisture-based

538 approach are potentially quite powerful. Relative to gauge measurements, the approach provides

539 areally averaged estimates that span much more of the globe. Relative to direct satellite-based

540 precipitation retrievals, the soil moisture-based estimates provide a time-integrated look at what

541 happened between the soil moisture retrievals (akin to gauge measurements, but for large areas)

542 – precipitation amounts falling between the "snapshots" of precipitation retrievals can be

543 captured with the soil moisture-based estimation approach.

544   We emphasize again that it is presumably by combining approaches, emphasizing the

545 strength of each one, that an optimal global precipitation dataset can be constructed. This idea

546 effectively underlies the aforementioned approaches of *Crow et al.* [2009, 2011], *Pellarin et al.*

547 [2013], *Wanders et al.* [2014], and *Zhan et al.* [2015], and it is perhaps the best way to consider

548 the SM2RAIN estimates examined here – not as a standalone precipitation dataset but as a

549 potential contributor to overall global precipitation estimation. The high skill levels shown in

550   Figs. 4 through 6, particularly for the L-band sensors, indicate that soil moisture retrievals do

551   show significant promise for making such contributions.

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647

Figure Captions

649

650   Figure 1. SMAP soil moisture retrievals (red dots) at a dry western US location plotted

651   alongside contemporaneous rain gauge-based precipitation data at the same location (blue

652   histogram bars). Soil moisture is in volumetric units, and precipitation is in mm/day. The

653   site, in northwestern Nevada, is characterized by scrubby vegetation.

654

655   Figure 2. Density of rain gauges underlying the CPCU precipitation dataset used to evaluate the

656   soil moisture retrieval-based precipitation estimates. Data were provided by CPCU in

657   units of # gauges / 0.5°×0.5° grid cell; the data were translated to the SMAP EASEv2 grid

658   at 36 km while retaining the original units.

659

660   Figure 3. a. Time series of SMAP soil moisture retrievals (red dots) at a representative location

661   in the central US. Plotted with dark blue and hollow histogram bars are the daily

662   precipitation rates estimated from these retrievals with the SM2RAIN algorithm, using (1).

663   Note that if consecutive retrievals are separated by, say, 3 days, the resulting single

664   precipitation estimate is assigned to each of the intervening 3 days. b. 5-day averages of

665   the SM2RAIN precipitation estimates (dark blue and hollow bars) and corresponding 5-

666   day totals from rain gauges at the same location (light blue solid histogram bars). For

667   display purposes, the SM2RAIN estimates are arbitrarily scaled by a constant factor in

668   each plot.

669

670   Figure 4. a. Square of the correlation coefficient (r^2) between 5-day precipitation totals from the

671   CPCU rain gauge network and corresponding SM2RAIN-based precipitation estimates

672   derived from SMAP (a), SMOS-A (b), SMOS-D (c) and ASCAT (d) soil moisture

673   retrievals. Gray coloring denotes correlations below 0.1; white coloring denotes locations

674   for which correlations are undefined due to limitations in data availability. Considering r^2

675   calculations over the 23 5-day segments of the full validation period (covering mid-June

676   through mid-October), r^2 values exceeding 0.13 are significantly different from zero at the

677   95% level, and those exceeding 0.23 are significantly different from zero at the 99% level;

678   note, however, that these significance levels must be adjusted in a very small subset of

679   locations (which varies with dataset) for which retrievals cover only a fraction of the

680   validation period.

681

682   Figure 5. As in Fig. 4, but for estimated and measured rain rates spatially aggregated to roughly a

683   1°×1° grid.

684

685   Figure 6. a. Averages (across the globe, over grid cells holding data for each dataset) of

686   precipitation estimation skill (r^2) at the 36-km resolution for the four different datasets,

687   binned according to rain gauge density (# gauges / 0.5°×0.5° grid cell, as in Fig. 2). That

688   is, an r^2 value at a given location is included in an average if the local rain gauge density

689   falls within the indicated range. b. Same, but for the aggregated ~100-km resolution

690   estimates shown in Figure 5. In the top panel, the number of grid cells contributing to a

691   given binned average is provided in brackets above the histogram bars.

692

693